Marine Reserves with Endogenous Ports: Empirical Bioeconomics of the California Sea Urchin Fishery

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Abstract *Marine reserves are gaining substantial public support as tools for commercial fisheries management. Harvest sector responses will influence policy performance, yet biological studies often depict harvester behavior as spread uniformly over fishing grounds and unresponsive to economic opportunities. Previous bioeconomic analyses show that these behavioral assumptions are inconsistent with empirical data and, more importantly, lead to overly optimistic predictions about harvest gains from reserves. This paper adds another layer of behavioral realism to the bioeconomics of marine reserves by endogenizing fisher home port choices with a partial adjustment share model. Estimated with Seemingly Unrelated Regression over monthly data, this approach allows simulation of both short- and long-run behavioral response to changes induced by marine reserve formation. The findings cast further doubt on the notion that marine reserves generate long-run harvest benefits.*

Key words Marine reserves, bioeconomics, seemingly unrelated regression, fishing port.

JEL Classification Code Q22.

Introduction

In May of 2000, President Clinton signed an executive order that directed the Departments of the Interior and Commerce to develop plans for an extensive network of marine protected areas in the coastal waters of the United States. The order was in direct response to claims by many influential marine scientists that our most im-

portant coastal ecosystems are potentially threatened by human actions, and that marine protected areas can preserve unique aquatic ecosystems and the non-consumptive services that they provide for present and future generations. On a deeper level, this order signals a fundamental change in marine policy that has the potential to affect commercial fisheries around the US in a profound way. The order explicitly acknowledges that marine resources are geographically diverse, as well as spatially interdependent, and that successful management of these resources should use spatially explicit tools. This distinctively spatial view of population dynamics embodies an important transformation in ecological paradigms, away from an older viewpoint that treats natural resources as uniformly distributed across space. Contemporary thinking emphasizes ongoing empirical findings about the patchiness and spatial heterogeneity of resources. Some recent ecological studies of the marine environment adopt metapopulation models that depict marine resources as discrete and heterogeneous patches of biomass that are linked through complex and variable oceanographic processes (Quinn, Wing, and Botsford 1993; Botsford *et al.* 1999).

Although non-market values may be at the heart of conservationists' support for marine protected areas, fisheries scientists also suggest that carefully designed marine reserves could benefit fisheries. In particular, many biological models predict potential harvest gains from managing with marine reserves (NRC 2001).[1] Typically these models simplify fishing behavior such that it is unresponsive to economic opportunities over time and space. Nevertheless, the possibility that biological benefits of reserves could be generated without costs (or even with benefits) to fisheries is a critical finding. The likelihood of anticipated fishery benefits may determine not only the economic efficiency of using reserves, but also the political feasibility of implementing them. The conventional wisdom in fisheries science is that there are many cases in which these harvest benefits will materialize.

However, economic research on marine reserves challenges this conventional wisdom in two crucial ways. First, the empirical economic literature on location choice unequivocally demonstrates that fishing effort is responsive to economic opportunities over time and space. Most of this research applies discrete choice modeling to target fishery choice (Bockstael and Opaluch 1983) or fishing ground choice at the trip level (Eales and Wilen 1986; Dupont 1993; Larson, Sutton, and Terry 1999; Curtis and Hicks 2000; Holland and Sutinen 2000; Mistiaen and Strand 2000; Smith 2002). Curtis and Hicks also calculate short-run welfare costs of closed areas, while Smith jointly models fishing participation and location choice such that total fishing effort and its spatial distribution are endogenous. Nonetheless, the literature on fishing grounds implicitly restricts the responsiveness of fishing effort by conditioning on each vessel's home fishing port. In this paper, we loosen this restriction by endogenizing fishing port.

Second, the conceptual and recent empirical bioeconomic literature on marine reserves shows that models with endogenous fishing effort reach substantially different conclusions about marine reserves than ones with exogenous effort. In contrast to purely biological models, conceptual bioeconomic studies of reserves identify a fairly restrictive set of conditions under which reserves generate net harvest gains. Holland and Brazee (1996), fixing total fishing effort before and after the policy change, show that joint harvest and conservation benefits are possible in the steady state under some circumstances regarding the initial (pre-reserve) levels of exploitation assumed. Reserves alone, however, do not address the underlying open-

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[1] The biological literature on marine reserves is voluminous. The NRC report summarizes the key findings to date. For more detail, see Sanchirico and Wilen (1999, 2001); Smith (2001, 2004); and Smith and Wilen (2003).

access forces that lead to overexploitation (Hannesson 1998). With an open-access model that allows for endogenous responses of fishing effort, Sanchirico and Wilen (2001) show that reserves are most likely to increase total harvest when the pre-re-serve fishery is severely overexploited.[2] Taken together, empirical location choice and conceptual bioeconomic studies suggest that since a reserve removes fishing opportunities, there will be some losses in the short run as fishermen are excluded from the reserve area. Moreover, since fishermen are responsive to economic returns, there will be some redistribution and possibly attrition in response to diminished opportunities. These changes in effort will alter fishing mortality and dynamics in a metapopulation, which will then change expected economic opportunities, and so on, in a complicated, dynamic, spatial process. The transition of such a system to its long-run steady state is likely to involve an initial period of losses, followed by recovery, and under some circumstances, a steady state with enhanced yields. Whether enhanced yields result is an empirical question, and predicting the ultimate consequences of reserves *ex ante* requires empirical bioeconomic modeling that tracks spatially explicit behavior.

Smith and Wilen (2003) bring empirical biological and economic spatial processes together by linking a metapopulation model with a repeated nested logit model of fishing location choice. They find that accounting for spatial behavior dramatically reduces the forecasted ability of marine reserves to actually enhance fisheries production. In comparison to biological models that assume uniform and unresponsive effort, their approach makes overall intensity of fishing effort and its spatial distribution endogenous. The costs and payoffs from fishing in various patches determine the pre- and post-reserve fishing effort distributions, which ultimately affect the likelihood that reserves can increase overall harvest. Smith and Wilen find dramatic differences between simulations that presume uniform and unresponsive effort and those that allow for endogenous effort. Both the spatial redistribution and the temporal attrition of effort reduce the set of circumstances under which reserves generate net harvest gains. Smith and Wilen focus on the trip level, taking trip origins as given. While this may suffice for short- and intermediate-term predictions of policy impacts, it misses additional important mechanisms by which a fishery might respond to marine reserves. In particular, in many fisheries, fishermen have the option to select home ports or ports of delivery. When vessels move from port to port, the set of accessible fishing grounds changes. Alternatively, when marine reserves are enacted, the relative payoffs available to fishermen based in different port locations will change, inducing further movement between ports over the long term. This mechanism is important to the political economy of reserves, since fishing communities and processing interests will likely oppose policies that reduce secondary activities in regions.[3] The primary contribution of this paper is to examine how robust the Smith and Wilen results are when fishing ports are endogenous.

The next section discusses the fishery background, data, and relevant biology for our case study of the northern California red sea urchin fishery. We also describe the bioeconomic simulation model in Smith and Wilen (2003) and highlight how endogenous fishing effort fits into the model. The following section develops and

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[2] While there are various modeling approaches, other papers in the economics literature also find that whether or not reserves generate net harvest gains depends on biological and economic features of the system (*e.g.*, Brown and Roughgarden 1999; Conrad 1999; Pezzey, Roberts, and Urdal 2000; Anderson 2002).

[3] This issue has been prominent in Alaska, for example, as processors and communities have fought rights-based programs, such as ITQs, on the grounds that they would radically alter processing needs and processing activities.

estimates a partial adjustment Seemingly Unrelated Regression (SUR) port share model and provides motivation for why port choice unfolds on a different time scale from choice of fishing ground. We compute short- and long-run spatial effort elasticities and characterize the additional responsiveness from modeling ports. Next, we integrate the port adjustment model into the bioeconomic simulation model and simulate short- and long-run impacts of marine reserves. The final section discusses the results.

The Case Study—the Northern California Red Sea Urchin Fishery

The northern California red sea urchin fishery is an ideal case in which to analyze marine reserves. First and foremost, urchin population dynamics are consistent with the biological structure that is favorable for management with reserves. Urchins are broadcast spawners and occur in "patches" or discrete subpopulations. The adults are sedentary, but the subpopulations are connected through larval dispersal. This means that heavily exploited populations may be able to rebuild when a reserve is established, and the benefits may feed the remaining areas that are open to fishing. In addition, biological returns to scale exist both in organism size and in density-dependent reproduction.[4]

In California, individual divers harvest sea urchins for their roe on day trips. Divers reach fishing grounds on 10–15 meter vessels. The vessels are small enough that it is possible to load them on trailers and drive to an alternative fishing port. Divers scrape urchins from rocky intertidal zones with hand-held rakes while breathing through an air hose that is attached to an on-board air compressor. Divers sell urchins dockside to processors located in various ports up and down the California coast. Freshness is extremely important for sea urchin roe, so whole urchins are typically processed within a day, packed in special wooden trays, and immediately flown to Japan.

The fishery is divided into northern and southern California partitions that are separated by the sea otter conservation area in central California. California Department of Fish and Game (CDFG) regulates the fishery with a combination of season closures (individual days, weeks, and months), minimum size limits, and limited entry licensing, though they are also considering the use of marine reserves. CDFG also maintains an extensive data set of logbook and landings ticket information that includes individual diver records for fishing dates, fishing locations, fishing ports, ex-vessel prices, and quantities caught.[5]

Although permit holders are free to move between northern and southern California, and many of them have spent time in both parts of the fishery (Smith 2001), we focus primarily on northern California because stock declines have been more dramatic in that region. Divers land sea urchins at six ports in northern California. From north to south, they are: Crescent City (CRC), Fort Bragg (FTB), Albion

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[4] As organism size increases, gamete production increases at an increasing rate. Thus, it may be beneficial to fish some patches and allow urchins to grow large in other patches. Density-dependent reproduction provides a similar argument for reserves. Since urchins are broadcast spawners, harvesting one sparsely populated area and allowing a reserve to become densely populated may produce more offspring (and harvest) than harvesting two moderately populated areas.

[5] While the quality of logbook data is often an issue for commercial fisheries, the information for calculating port shares and expected port revenues comes from landings tickets that record actual sales. We, thus, believe that our data are very high quality. For the fishing location choice model in Smith and Wilen (2003), the key field used from logbook data is the location recorded in degrees and minutes of latitude. We believe that the precision of latitude minutes, while sufficient for our analysis, is not so detailed that divers have any incentive to misreport.

(ALB), Point Arena (PTA), Bodega (BOD), and Half Moon Bay (HMB). Given the rugged coast of northern California and the rapid quality decay of fresh sea urchins, these ports are really the only feasible alternatives for landing urchins.[6] More than 90% of catch is landed at the four ports in the middle. Figure 1 shows the location of these ports. Since divers make exclusively single-day trips, one can see immediately that a diver's port ultimately limits the feasible set of possible fishing location choices, in both the short and long run. Figure 2 illustrates the pattern of revenue shares in each port over time.

The simulation model in Smith and Wilen (2003) captures dynamic and spatial features of the sea urchin biological and oceanographic system, as well as spatial dimensions of the harvest sector. First, the process of building up a subpopulation from an overharvested state may generate returns to scale in biological production due to organism size or density-dependent spawning. Second, sinks and sources in the dispersal of organisms may also generate returns to scale or exacerbate existing ones, particularly when adult organisms are sedentary and only larvae disperse. Third, there may be some ecological value of preserving a full, natural life cycle, which a marine reserve can ensure. Combining these features requires a model with multiple subpopulations that allows for larval dispersal and captures age- and size-structure within each subpopulation. Botsford *et al.* (1999) develop a metapopulation model that captures all of these features, and Smith and Wilen (2003) and Wilen *et al.*
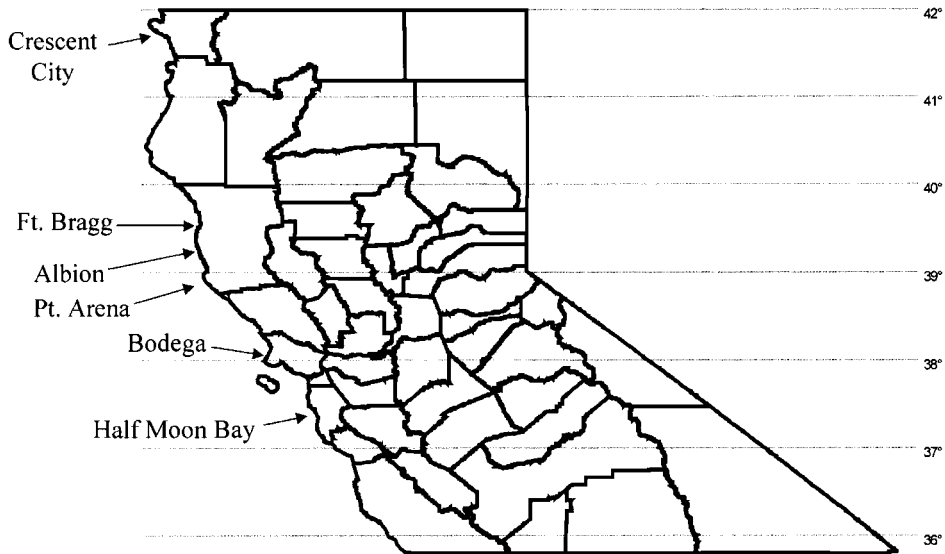

Figure 1. Northern California Sea Urchin Ports

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[6] It may be physically possible to land sea urchins at ports in San Francisco, but this never occurs in our data set. Most of the urchin fishing grounds are north of the peninsula, and the costs of mooring vessels in the San Francisco Bay Area could be a factor.
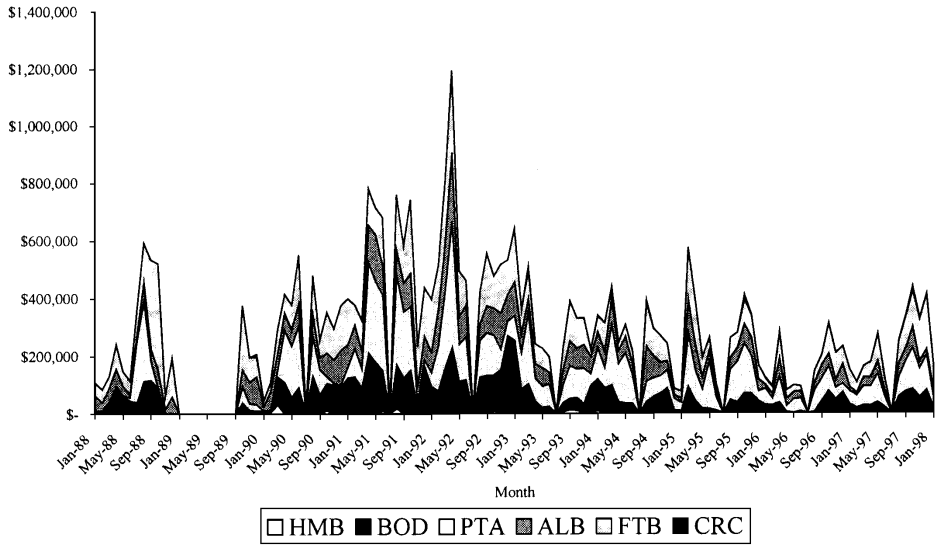
Figure 2. Northern California Sea Urchin Dockside Revenues

(2002) adapt it to include economic behavior. While these papers describe the model in detail, we briefly outline its analytical structure here.

In this model, the northern California red sea urchin fishery consists of 11 discrete age- and size-structured subpopulations linked by a dispersal matrix. Each separate subpopulation has a size structure described by a von Bertalanffy equation, so that the size of an individual of age a in patch j is given by:

$$Size_{j,a} = L_\infty^j (1 - e^{-k_j a}), \tag{1}$$

where a is a monthly time index from 1 to 360, and L_∞^j and k_j are patch-specific growth parameters. Populations are then aged by advancing the abundance values for each month to the next older month so that $A_{i,a}$ is a function of $A_{i,a-1}$, where A denotes the number of organisms in the cohort. After the populations are aged, the numbers surviving in the population are computed, along with the catch. A Beverton-Holt mortality relationship determines survivors, which embeds both patch-specific natural mortality rates, m_j, as well as fishing mortality rates, f_j, if the size is above the minimum size limit, L_{limit}. We link the economic model of diver behavior to the population model by making monthly fishing mortality rates a function of predicted diver trips. Accounting for both natural and fishing mortality, survival of the number of individuals to age $a + 1$ becomes:

$$A_{j,a+1} = \begin{cases} A_{j,a} e^{-m_j} & \text{if } Size_{j,a} < L_{limit} \\ A_{j,a} e^{-m_j - f_j} & \text{if } Size_{j,a} > L_{limit} \end{cases}, \tag{2}$$

and total catch (C) consists of the sum of harvests of all sizes greater than the minimum size over all patches, which is:

$$C = \sum_{j=0}^{10} \sum_{a=0}^{360} \frac{f_j}{m_j + f_j} \left[1 - e^{-(f_j + m_j)}\right] w \, Size_{j,a}^b \, A_{j,a}, \; \forall \; Size_{j,a} > L_{limit}, \tag{3}$$

where w and b are allometric parameters relating weight and urchin test diameter. These parameters essentially convert number of organisms of each size to an aggregate measure of biomass, and harvest is a function of that biomass based on the fishing mortality parameters f_j. The allometric parameters give rise to the possibility of an increasing returns production technology because $b > 1$ is the usual case, which means that the second derivative of catch with respect to size is positive.

The metapopulation model also computes egg production, larval dispersal, settlement, and survival. Egg production in the model ultimately determines how many larvae are produced and is computed after survival has been calculated for each month.[7] If the month is a spawning month, then egg production in patch j is computed with:

$$e_j = \sum_{a=0}^{a=360} \alpha x^\beta A_{j,a} \quad \text{where} \quad x = \begin{cases} Size_{j,a} & \text{if } Size_{j,a} > L_{maturity} \\ 0 & \text{if } Size_{j,a} < L_{maturity} \end{cases}. \tag{4}$$

This equation sums the egg production from each size class, where there is only positive production for sizes greater than the size at reproductive maturity. The exponent on size (β) is greater than one, since egg production is increasing and convex in organism size. Thus, the egg production relationship gives rise to another dimension of increasing returns production technology. For each month of the egg production period, a fraction of egg production survives and disperses according to:

$$\mathbf{s}^{in} = p\mathbf{De}. \tag{5}$$

This 11×1 vector gives the array of settlement associated with the array of egg production from the system, modified by the survival probability, p, and distributed by the dispersal matrix, $\mathbf{D}$. The number that actually settle successfully follows the following stock-recruitment function:

$$s_j^{out} = \frac{s_j^{in}}{a^{-1} + c^{-1} s_j^{in}}. \tag{6}$$

To complete the bioeconomic model, fishing behavior is linked to the metapopulation model by endogenizing the fishing mortality coefficients. Predicted trips are converted to time- and location-specific fishing coefficients, f_{jt}, by the following:

$$f_{jt} = (y_{jt})hq, \tag{7}$$

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[7] Total larvae, in turn, can be thought of as a measure of the biological system's resilience to environmental or harvesting shocks. Since patches are connected through larval dispersal, as long as there is high egg production in the system, heavily exploited areas can be repopulated.

where y_{jt} is trips to location j at time t, h is hours per trip (assumed constant in our simulations), and q is a catchability coefficient (to be calibrated to the actual fishing data).[8] Combined with an assumed price of \$1 per pound, these fishing mortalities are fed back into the model to predict expected revenues and y_{jt} in the next period.

The total predicted trips (y) in each location j in month t is the number of divers in each port (d_p) times the probability of visiting the patch from that port at t (p_{pjt}) multiplied by the number of choice occasions in that month (o_t):[9]

$$y_{jt} = o_t \sum_{p=1}^{4} d_p p_{pjt}.$$ (8)

The Smith and Wilen (2003) model estimates p_{pjt} using repeated nested logit but assumes that the total number of active divers and the distribution of these divers across ports will not change over the course of time. The key difference between the model with and without port switching is that the model with port switching computes the endogenous d_p's in equation (8). Thus, our empirical focus in this paper is on how to endogenize the d_p's.

Spatial Choice over the Short and Long Run — Modeling Two Time Scales

Previous econometric work on urchin diver behavior focuses on a detailed depiction of the participation and fishing location choices (Smith 2002; Smith and Wilen 2003; Wilen *et al.* 2002), using a repeated nested logit model to analyze daily fishing decisions. For each fishing day, a diver chooses whether or not to go fishing. If he fishes, he also chooses where to fish from a set of discrete fishing locations, which we denote as patches to be consistent with the metapopulation literature. In all of this analysis, a longer travel distance from a particular port reduces the probability of visiting a patch, and a higher patch-level revenue increases the probability of visiting a patch. With this nesting structure, higher revenues also increase the overall level of participation.

All of the individual choice models estimated in previous work are conditional on the port of origin of each diver. This implies that a diver's home port determines the travel distances to the portfolio of patch options available to him/her. But when economic and biological policies change, we would also expect that the relative attraction of locating in a particular port would change. So in the long run, we would anticipate that divers could choose port location, as well as make daily participation

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[8] The actual number of dive hours per trip exhibits considerable heterogeneity in sample, but attempts to explain it have not been successful. It appears to be random, and we assume that averaging across individuals is an appropriate proxy. One specific analysis that is undertaken is to see if hours per trip can be explained by travel distance. The idea is that larger travel distances allow less time for diving. The R^2 value is 0.0017. A statistically significant relationship is found, but it is quantitatively insignificant. The marginal decrease in hours per trip for a 69 mile travel distance was .013. That converts to about one second less diving for one mile of extra travel. There is rounding in the hours reported, which introduces some error in this measure of effort. However, there is no reason to believe that it would bias results in one direction or the other, or for that matter, that it would be correlated with travel distance. The most likely explanation for this result is simply that diving is physically tiring, and individuals on a trip do not exceed a certain dive length. In that sense, travel time and dive times are separate decisions.

[9] The choice occasions for a given month are determined by the season closure regulations. For northern California, all of July is closed. In June and August, the season is three days per week but closed one week each month. In May and September, the season is four days per week but closed one week each month. In April and October, the season is four days per week, and the rest of the year, all days are open.

and patch-choice decisions from each port. Port choice is a different type of discrete decision than participation and location choice, however. For the latter, the time step is naturally a daily one. Is it worth fishing today or not? If so, is it better to go to patch 1 or patch 2, *etc.*? Though port choices are also discrete decisions, it is not realistic to apply a daily time step to these decisions.

Port switching realistically involves a longer time step for two reasons. First, it is clearly infeasible to switch ports every day, particularly if a diver switches from a port in southern California to one in northern California. Second, switching ports entails lumpy costs, including the potentially very significant cost of moving one's home and family. In general, we would expect an individual to switch ports if the discounted expected return differential (comparing the new location to the old location) exceeds the cost of switching. That is, a switch will occur if:

$$\sum_{\tau=t}^{T} \rho^{(\tau-t)} E(\pi_{itm} - \pi_{itl}) \geq c_{it,m \to l}, \tag{9}$$

where m and l index ports, $m{\to}l$ indicates moving from m to l, ρ is the discount factor, π is net rents in a location, and c is switching cost.[10] Note that costs and revenues are subscripted by i to denote individual-specific values. One would expect that switching costs are heterogeneous across the population of harvesters for a variety of reasons. Some individuals have families, while others do not. Divers likely have heterogeneous economic opportunities outside the fishery. What we observe in the data actually suggests that expected revenue streams are also heterogeneous across individuals. Specifically, there are days in which at least one individual switches from port A to port B, while another individual switches from port B to port A.[11] Assuming that switching costs are positive, it must be that the expected revenue streams for these two individuals are different.

Because switching costs are lumpy and rent differentials may be transitory, we expect that port shares will respond sluggishly to contemporaneous rent differentials across space. Beyond personal considerations, such as family, there are several other reasons for lumpy switching costs. One possibility is long-term contracts for mooring a vessel. Another explanation is contractual relationships between a diver and a processor. Although we do not observe long-term diver-processor contracts in our data set, long-term informal relationships between divers and processors exist whereby divers have persistent long-term relationships with particular processors/dealers.[12] Thus, a contemporaneous rent differential is not necessarily enough for an individual to change ports. If the rent differential persists or widens over time, the expected rent differential stream would grow and eventually lead to a switch.

A partial adjustment model is one way to model sluggish adjustment empiri-

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[10] Throughout this paper, we assume that individual divers are price takers. Though we do not test this assumption, we note that there are over 500 individual urchin divers that participate in the fishery over the period of our sample.

[11] For instance, on 11/17/88 one diver switched from Albion to Fort Bragg, while another diver switched from Fort Bragg to Albion. Similarly, on 9/1/91 one diver switched from Bodega to Point Arena, while four divers switched from Point Arena to Bodega.

[12] One indication of these long-term relationships is the share of business that an individual diver does with the dealer to whom he most often sells his catch. There are 275 divers with a least 25 dives in northern California. For each diver, we identify the top-ranked dealer as the dealer that the diver sells to the most number of times. On average, these divers sell a share of 0.545 of their landings to each diver's top-ranked dealer. The standard deviation is 0.204. Expanding the set of divers to ones with at least 10 dives in northern California, the mean and standard deviation are 0.606 and 0.235, respectively. Thus, diver-dealer relationships are clearly important.

cally.[13] In this setting, the target share, s^*, of divers in each port ($m = 1, \ldots, M$) is a function of the expected net rents (Π) in each port and parameters (θ). Following the treatment in Greene (1993), we have:

$$s^*_{mt} = f^m(\Pi_{1t}, \ldots, \Pi_{Mt}; \theta_{m1}, \ldots, \theta_{mM}), \, m = 1, \ldots, M, \tag{10}$$

or in matrix form:

$$\mathbf{s}^*_t = \mathbf{f}(\Pi_t; \Theta). \tag{11}$$

Actual share adjusts to the difference between the current period's target share and the previous period's actual share.[14] Assuming an additive error term, this leads to the following:

$$s_{mt} - s_{mt-1} = (1 - \lambda)(s^*_{mt} - s_{mt-1}) + \varepsilon_{mt}, \, m = 1, \ldots, M. \tag{12}$$

Substituting equation (10) into (12) produces the autoregressive form of the model:

$$s_{mt} = \lambda s_{mt-1} + (1 - \lambda)f^m(\Pi_{1t}, \ldots, \Pi_{Mt}; \theta_{m1}, \ldots, \theta_{mM}) + \varepsilon_{mt}. \tag{13}$$

Implicitly, this model averages over the heterogeneity that exists across individuals in both their assessments of rent differentials and in their lumpy switching costs.

Empirically, we do not observe actual expected net rents across space and time. We assume that expected revenues are an adequate proxy for rents because the two measures are highly correlated.[15] Fixed costs that vary across space do not vary across time because they partly involve features of the coastal geography, and variable costs that do change over time are likely to be correlated across space (*e.g.*, fuel costs and wages in other fisheries). Thus, changes in revenues likely capture changes in rents across space and time. Suppose that the forcing equation in (13) is a function of revenues that is linear in parameters:

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[13] We do not attempt to model individual expectations, nor do we model forward-looking behavior. In some sense, partial adjustment is a reduced-form model of the economic dynamics. Partial adjustment is also difficult to distinguish econometrically from adaptive expectations, which provides one expectations-based explanation for the dynamics that we see. Nevertheless, we argue that this model is justified because lumpy switching costs are the most important feature of port dynamics.

[14] Though a rent equilibrium in this fishery is a complex bioeconomic phenomenon, the share model presumes simply that past rents carry the relevant information for port choice and that the fleet essentially makes sequentially myopic decisions. A reviewer points out that a Lucas Critique may apply to the policy simulations later in the paper. We agree that this is a valid concern, but argue that the benefits of our approach outweigh the drawbacks. First, in spite of existing regulations, some degree of open access forces persists in the urchin fishery. Thus, individuals cannot fully appropriate gains from forward-looking actions—particularly from restricting their own harvests—and it is reasonable to assume some form of sequentially myopic decision making. Second, some simplification of the economic dynamics is necessary because a fully structural forward-looking model with spatial biological features is simply intractable. Finally, even if a fully structural metapopulation econometric model were tractable, it is unreasonable to assume that individual fishermen have this level of knowledge of the biological system. Most of our biological parameters are not estimated from the fishing data, but instead come from a large set of independent biological and oceanographic studies.

[15] For the estimations below, we assume that expected revenues are backward-looking monthly averages in the port. This is consistent with the monthly averages by patch in Smith and Wilen (2003) and allows for a monthly time step in the bioeconomic simulations. Given that the simulation model is deterministic, a steady state is approached when revenues in each patch (and therefore in each port) are in equilibrium long enough to bring target and actual shares in alignment.

$$f^m(\Pi_{1t},...,\Pi_{Mt}; \theta_{m1},...,\theta_{mM}) = \alpha_m + \sum_{k=1}^{M} \gamma_{mk}g(R_{kt}), \, m = 1, ..., M. \tag{14}$$

The α's account for non-fishery benefits of being at a particular port that do not change over time. Note that it is still possible to estimate the model as linear in the parameters but to nonlinearly transform the data. As such, a function $g(.)$ is included in equation (14), since the relationship between shares and revenues does not have a definitive curvature *a priori*. The function $f^m(.)$ in equation (14) leads to a system of M equations with each equation defined by:

$$s_{mt} = (1 - \lambda)\alpha_m + \lambda s_{mt-1} + (1 - \lambda)\sum_{k=1}^{M} \gamma_{mk}g(R_{kt}) + \varepsilon_{mt}. \tag{15}$$

The virtues of this model are that it can be estimated in a manner consistent with the partial adjustment model, above, and one can impose restrictions such that the long-run expected shares sum to one. The economic content of the model is preserved in that shares respond unambiguously to revenue changes across space and time.[16] The full model of choice with port switching is depicted in figure 3. For simplicity, we depict only two ports in northern California and three patches. The patch choices closest to the relevant port are in bold. Divers in each port are assumed to make fine
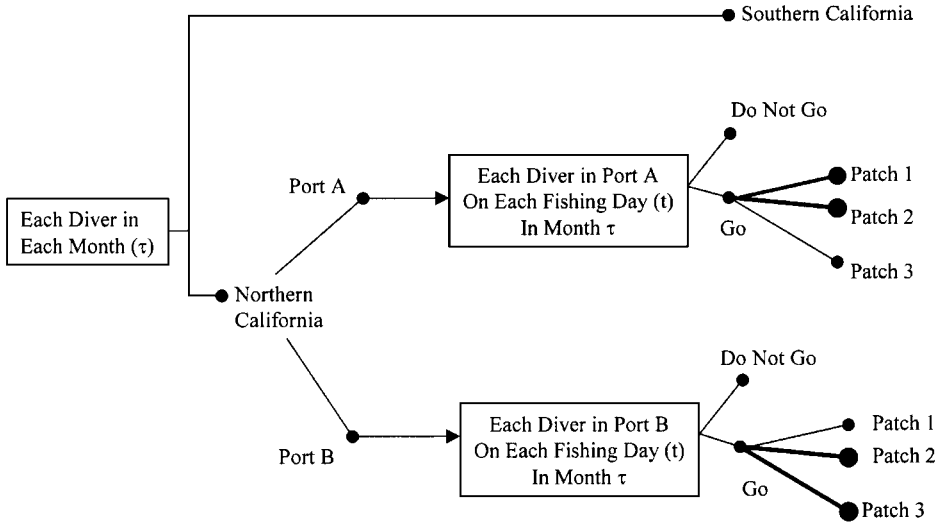
Figure 3. Urchin Diver Decision Tree

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[16] The main drawback is that the model can predict individual shares outside the unit interval. Since we can impose that they sum to one in the long run, the practical significance of this problem is that negative shares can be predicted. In the event of a negative share, one would have to make an *ad hoc* adjustment to the predicted shares used in the bioeconomic simulation model.

time scale decisions (daily) about whether to fish and, if so, where. On a coarser time scale (monthly) divers also make decisions about whether to switch to different ports within northern California, and also about whether to locate and fish in northern or southern California.

Because there is substantial geographic separation between the northern and southern California fisheries, we estimate port shares in a two-step process. First, divers are allocated between northern and southern California with one partial adjustment model. Then, a separate set of equations is estimated to allocate northern California divers to the different northern California ports. This nesting permits the speed of adjustment to differ for decisions about switching ports within northern California and decisions about switching from (to) northern to (from) southern California. For the south/north share equation, expected revenues are computed by averaging actual lagged revenues across all ports.

Before turning to restrictions on the linear model, it is worthwhile to explore the functional form for the expected revenue terms. To this end, Box-Cox transformations are run on each port equation. Thus, for each equation in (15), a parameter η is estimated to define the $g(.)$ such that:

$$g(R_{kt}) = \frac{(R_{kt})^{\eta} - 1}{\eta}. \tag{16}$$

Based on the Box-Cox estimations,[17] we proceed with the following functional form for the partial adjustment model:

$$s_{mt} = (1 - \lambda)\alpha_m + \lambda s_{mt-1} + (1 - \lambda)\sum_{k=1}^{M} \gamma_{mk} \ln(R_{kt}) + \varepsilon_{mt}. \tag{17}$$

There are essentially two systems to estimate: one for the north/south switching and one for the switching within the north. One immediate restriction that we might impose is that the speed of adjustment is the same within each system (but not necessarily across systems). This suggests that the inertia against switching ports is the same for similar decisions. In general, we expect that north/south switching must overcome more inertia than switching within the north because the former decision is more costly.[18] A second type of restriction is based on the idea that marginal effects of revenues must add up across equations. When revenues go up in one port, *ceteris paribus*, we expect an increase in that port's share. This increase must come from other ports, since we model the region decision and the port decision within a region as recursive. Thus, a share increase from a 1% increase in revenue must equal

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[17] One can then test η against different values. For instance, if the null hypothesis of $\eta=1$ is not rejected, then the model is linear in variables. Alternatively, if the null hypothesis of $\eta=0$ is not rejected, then the model is linear in the natural logs of the variables. There are seven total equations, one for the north/south share and six northern port share equations. We estimate these models separately before proceeding to model the system. Due to multicollinearity combined with the highly nonlinear nature of the Box-Cox transform, four models are singular. However, for the three models that do converge without singularities, we fail to reject the hypothesis of $\eta = 0$. These models are Albion, Bodega, and Crescent City. The t-statistics are –1.23, 0.75, and 0.24, respectively.

[18] By restricting speed-of-adjustment parameters within each system, it is possible to impose adding up restrictions in a linear manner. Similarly, it is also possible to impose a linear restriction that long-run expected shares sum to one. Although we believe that this is *a priori* justification for this restriction, we also test the restriction for the northern California system. The test statistic is 0.3527 and is distributed $F_{4,515}$. The critical value is 2.39. Thus, we fail to reject the restriction of same adjustment parameter within the northern California system.

the total share losses from that increase in revenue. That is,

$$\sum_{m=1}^{M} \gamma_{mk} = 0, \tag{18}$$

where m indexes across ports and k is the index for each expected revenue term. These restrictions identify the model such that one equation must be dropped from each system.[19]

Share Model Estimation: Between Northern and Southern California

We estimate the north/south switching model on a monthly time step using data from 1988–98. The total sample size of 111 represents a 130-month sample period, subtracting 18 months of season closures, and dropping the first month to initialize the lagged share variable. Table 1 summarizes the results. All coefficients have their expected signs, and λ lies in the unit interval. The interpretation of the revenue coefficients is simply that the share of divers in southern California increases in response to expected revenues in that region and decreases in response to expected revenues in northern California. Interestingly, the expected revenue coefficients are very similar in magnitude. We test that these coefficients are the same using an F test. The test statistic is 0.0446, the critical value (for 5% confidence) is 3.93. Thus, we fail to reject the hypothesis that the coefficients are the same. Combined with the cross-equation restrictions, this suggests that the southern California share increase from a 1% increase in R_{SOC} is the same as the northern California share increase from a 1% increase in R_{NOC}.

Another noteworthy aspect of these results is that the estimated λ — 0.86 — is close to one. In a partial adjustment model, a λ of zero implies instantaneous adjustment. As λ approaches one, the speed of adjustment is slower. That is, in this model the optimal shares of divers in northern and southern California respond slowly to structural changes in the relative profitability of diving in these regions. This result is not surprising given the geographic separation of the regions.

Table 1
South/North Switching OLS Model of Port Shares

Variable	Parameter	Coefficient	t-statistic
Constant	α	0.028061	0.151
Lagged SOC Share	λ	0.861212	17.242**
$\ln(R_{SOC})$	γ_{SOC}	0.056192	1.6678*
$\ln(R_{NOC})$	γ_{NOC}	–0.050767	–1.908*
R^2	0.8231		
N	111		

Notes: ** indicates significant at the 5% level and * indicates significant at the 10% level.

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[19] For the north/south switching model, this means that there is just one equation to estimate. The reason is that there are six total parameters, three restrictions, and the dependent variables always sum to one. Hence, not dropping an equation creates a singularity in the covariance matrix.

Share Model Estimation: Within Northern California

In northern California, there are six ports, and the dependent variable is the share of northern California divers. There are six equations, forty-eight parameters, five restrictions on λ, and six restrictions on the γ's. Now suppose that all revenues are the same across ports. We expect that the revenue terms within an equation might offset each other, but that real differences in opportunities across ports persist. For the long-run expected shares to sum to one when revenue effects are offsetting, the following restriction must hold:

$$\frac{\sum_{m=1}^{M} \alpha_m}{(1 - \lambda)} = 1, \tag{19}$$

which can be rewritten as a linear restriction on the α's and λ. By dropping one equation, we can estimate the parameters using SUR. The virtue of SUR in this setting is two-fold: it permits easy implementation of cross-equation restrictions, and it is efficient relative to individual Ordinary Least Squares (OLS) estimations because it allows for contemporaneous correlation. The parameters for the dropped equation can be recovered from the restrictions on the γ's, the λ's, and the α's.

Table 2 contains the SUR results for HMB, BOD, PTA, ALB, and FTB along with the recovered parameters for CRC.[20] Note first that the estimated λ is much smaller than the λ from the north/south system, implying that the speed of adjustment is much faster within the northern California system than between the northern and California systems. It is much less costly to switch from, say, Fort Bragg to Albion than to switch from Fort Bragg to southern California. The implication is that port shares within northern California respond more quickly to structural changes in expected revenues.

For the most part, the expected revenue coefficients are in accordance with our prior beliefs. Of the five estimated own-revenue coefficients, three are positive and statistically significant, one is positive and not significant, and the other is negative and not significant. Many of the off-diagonal revenue coefficients are negative, and some are statistically significant. Only two of the off-diagonal coefficients have the wrong (*i.e.*, positive) sign and are statistically significant ($\gamma_{BOD,FTB}$ and $\gamma_{ALB,CRC}$). These aberrations are likely the result of multicollinearity in the expected revenue terms. Overall, in spite of the CRC expected revenue coefficient, the ALB model appears to work best. The intercept and own-revenue coefficients are positive and significant, two neighboring revenue coefficients are negative and significant, a revenue coefficient two ports away is also negative and significant, and a revenue coefficient three ports away is negative though not significant.[21]

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[20] All estimates were obtained using the SYSLIN procedure in SAS and imposing the relevant cross-equation restrictions.

[21] The SUR model for northern California also appears to work well for predicting shares. By construction, the shares sum to one. For BOD, PTA, ALB, and FTB, the predicted shares are always in the unit interval. The HMB predicted share is positive on 106 occasions out of 111. The CRC predicted share is positive on 94 occasions out of 111. The minimum predicted share for either port is –0.0048, so there is little practical significance in adjusting port shares in the simulation model when a negative prediction results.

Table 2
SUR Results for Northern California Port Switching

Variable	Parameter	Coefficient	t-statistic
Diver share for:			
Half Moon Bay			
Constant	α_{HMB}	0.036008	0.71
Lagged HMB Share	γ	0.436385	10.37**
$\ln(R_{HMB})$	$\gamma_{HMB,HMB}$	0.009295	2.29**
$\ln(R_{BOD})$	$\gamma_{HMB,BOD}$	−0.011418	−1.13
$\ln(R_{PTA})$	$\gamma_{HMB,PTA}$	−0.001983	−0.24
$\ln(R_{ALB})$	$\gamma_{HMB,ALB}$	0.00211	0.16
$\ln(R_{FTB})$	$\gamma_{HMB,FTB}$	−0.006573	−0.57
$\ln(R_{CRC})$	$\gamma_{HMB,CRC}$	0.006441	1.40
Bodega			
Constant	α_{HMB}	−0.588058	−4.38**
Lagged BOD Share	λ	0.436385	—restricted—
$\ln(R_{HMB})$	$\gamma_{BOD,HMB}$	0.005392	0.50
$\ln(R_{BOD})$	$\gamma_{BOD,BOD}$	0.020226	0.76
$\ln(R_{PTA})$	$\gamma_{BOD,PTA}$	0.038562	1.79*
$\ln(R_{ALB})$	$\gamma_{BOD,ALB}$	−0.093301	−2.71**
$\ln(R_{FTB})$	$\gamma_{BOD,FTB}$	0.143569	4.69**
$\ln(R_{CRC})$	$\gamma_{BOD,CRC}$	−0.00833	−0.69
Point Arena			
Constant	α_{PTA}	0.524777	2.60**
Lagged PTA Share	γ	0.436385	—restricted—
$\ln(R_{HMB})$	$\gamma_{PTA,HMB}$	−0.0183	−1.15
$\ln(R_{BOD})$	$\gamma_{PTA,BOD}$	−0.001566	−0.04
$\ln(R_{PTA})$	$\gamma_{PTA,PTA}$	0.068064	2.13**
$\ln(R_{ALB})$	$\gamma_{PTA,ALB}$	−0.065888	−1.29
$\ln(R_{FTB})$	$\gamma_{PTA,FTB}$	−0.05216	−1.14
$\ln(R_{CRC})$	$\gamma_{PTA,CRC}$	0.000851	0.05
Albion			
Constant	α_{ALB}	0.424906	2.99**
Lagged ALB Share	γ	0.436385	—restricted—
$\ln(R_{HMB})$	$\gamma_{ALB,HMB}$	−0.013528	−1.19
$\ln(R_{BOD})$	$\gamma_{ALB,BOD}$	−0.056048	−2.00**
$\ln(R_{PTA})$	$\gamma_{ALB,PTA}$	−0.043831	−1.93*
$\ln(R_{ALB})$	$\gamma_{ALB,ALB}$	0.103488	2.86**
$\ln(R_{FTB})$	$\gamma_{ALB,FTB}$	−0.067638	−2.10**
$\ln(R_{CRC})$	$\gamma_{ALB,CRC}$	0.033086	2.56**
Fort Bragg			
Constant	α_{FTB}	0.15705	0.77
Lagged FTB Share	γ	0.436385	—restricted—
$\ln(R_{HMB})$	$\gamma_{FTB,HMB}$	0.019082	1.17
$\ln(R_{BOD})$	$\gamma_{FTB,BOD}$	0.048374	1.17
$\ln(R_{PTA})$	$\gamma_{FTB,PTA}$	−0.064931	−1.99**
$\ln(R_{ALB})$	$\gamma_{FTB,ALB}$	0.047362	0.90
$\ln(R_{FTB})$	$\gamma_{FTB,FTB}$	−0.011484	−0.25
$\ln(R_{CRC})$	$\gamma_{FTB,CRC}$	−0.027462	−1.48

(Continued on next page)

Table 2
SUR Results for Northern California Port Switching (Continued)

Variable	Parameter	Coefficient	t-statistic
Diver share for:			
Crescent City			
Constant	α_{CRC}	0.008932	—recovered—
Lagged CRC Share	γ	0.436385	—recovered—
$\ln(R_{HMB})$	$\gamma_{CRC,HMB}$	–0.001941	—recovered—
$\ln(R_{BOD})$	$\gamma_{CRC,BOD}$	0.000432	—recovered—
$\ln(R_{PTA})$	$\gamma_{CRC,PTA}$	0.004119	—recovered—
$\ln(R_{ALB})$	$\gamma_{CRC,ALB}$	0.006229	—recovered—
$\ln(R_{FTB})$	$\gamma_{CRC,FTB}$	–0.005714	—recovered—
$\ln(R_{CRC})$	$\gamma_{CRC,CRC}$	–0.004586	—recovered—
R^2 (system weighted)	0.357		
n	555		

Notes: ** indicates significant at the 5% level and * indicates significant at the 10% level.

Spatial Fishing Effort and Marine Reserve Simulations

In this section, we adapt the empirical results from the previous section to the integrated bioeconomic simulation model. We compare the economic responsiveness of urchin divers when port switching is modeled to the economic responsiveness when just daily participation and fishing location choice are modeled. To this end, we first derive and compare effort elasticities with port switching to effort elasticities that account only for trip-level spatial decisions based on the Smith and Wilen (2003) repeated nested logit model. We then simulate marine reserve outcomes.[22]

Fishing Effort Elasticities

We ultimately measure fishing effort at the patch level. How does patch-level effort respond to an increase in patch-specific revenue? To answer this question, we compute elasticities for trips to different patches with respect to changes in revenues under different assumptions about spatial mobility. The computed elasticities tell us the percentage change in fishing pressure at a given location in response to a 1% increase in expected revenues in that location. Adding the possibility of port switching over a longer time scale permits us to distinguish between short-run and long-run elasticities, which to our knowledge has never been done in models of fishing loca-

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[22] Results from the repeated nested logit estimation are in Smith and Wilen (2003). To summarize, the model includes over 400,000 individual choice occasions. The set of participation choices is constructed based on the actual active divers on each day and netting out the partial season closures. Variables affecting participation alone include a dummy (for Friday, Saturday, and Sunday) and three weather indicators (wave height, wave period, and wind speed). Variables that influence location choice include travel distance (from port to patch) and patch-specific expected revenues (backward-looking monthly averages in the patch for the entire fleet). The nested logit inclusive value coefficient folds the location branch back into the participation decision. As such, an increase in patch-specific expected revenues (or a decrease in distance, which would be the case in the event of a port switch) also increases overall participation. All coefficients are significant at the 1% level.

tion choice. When revenues in a patch increase (or decrease), there are four avenues through which effort in that patch responds. First, an increase in revenue makes the patch more favorable relative to other patches and draws effort in from other patches. Second, an increase in revenues also makes fishing participation overall more profitable and increases average participation. Some of this increase is allocated to the patch. Third, a revenue increase makes choosing the port nearby more attractive relative to others and leads to some short-run port switching. Finally, the sluggish responses in port switching draw even more divers over the long run to the port and the nearby patches when revenue in one patch increases.

To operationalize elasticities and the simulation model, we make several simplifying assumptions. First, we reduce the model to one with just the four main northern California ports. Second, we note that port choice only affects travel distances to patches, and all other variables that influence choice probabilities are the same across different individuals. Thus, the stratification of choice probabilities in the simulation model is done only in one dimension. Third, we must assume something about the total number of urchin divers across northern and southern California. Substantial entry and exit behavior takes place over the period during which we must calibrate the simulation model. To handle this changing total number of divers, we stop and restart the simulation model several times, changing the default total number of divers to match closely the actual number of participants in the fishery. Once we are past the sample period, we do not know how many active divers will be in the fishery. However, the limited entry program includes a mechanism that will steer the long-run diver count to a target level of 300. Thus, to simulate out-of-sample, we assume that the long-run number of harvesters approaches the limited entry target of 300.[23]

Given the assumptions above, the first step is to predict the total number of divers in northern California. With the limited entry program, there are approximately 300 total divers in the fishery in the long run in both northern and southern California.[24] We allocate the 300 divers between northern and southern California using the results of the regression in table 1 and fixing southern California revenues.[25] Since we fail to reject the hypothesis that $\gamma_{NOC} = -\gamma_{SOC}$, we use a single revenue parameter here.

We next allocate predicted northern California divers among the northern California ports using a stylized version of the regression results in table 2.[26] The

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[23] By allowing share of northern California divers to adjust, divers harvesting from the northern California metapopulation is effectively endogenous.

[24] Average participation rates do not change substantially over the sample period, which justifies the 300-diver long-run assumption. For the calibration of the simulation model, we use actual number of divers because there were substantially more participants in the fishery going through a period of attrition. Though it is possible that the total active divers could drop below 300, the assumption is that decreases in profitability and the subsequent decreases in participation in the nested logit model would mimic this attrition.

[25] This approach is evaluated over the sample period using the mean southern California revenue per trip and predicted and actual southern California shares in the lagged share variable. Both methods track the share trends. Using actual shares rather than predicted does a better job, of course, but using predicted shares only misses the seasonality of the process.

[26] The reason that the model is stylized is twofold. First, although the port selection model is estimated over six ports and includes Half Moon Bay and Crescent City, the focus here is only on the four main ports of northern California. This is done for simplicity and to reduce the dimensionality of the model, but it is also justified because Half Moon Bay has limited activity and is separated from the rest of the fishery by most of the San Francisco Bay Area. Crescent City has even less fishing activity and is extremely far from the next nearest port. Moreover, activity in Crescent City, if linked to another fishing port for sea urchin, may be linked more closely to the sea urchin fishery in Oregon. Second, the model is stylized because not all of the port selection regression results are economically sensible. In particular, some of the off-diagonal coefficient signs are opposite of what we expect, possibly due to severe multicollinearity. The components of these revenues are correlated as well. Prices are highly correlated, presumably as a result of market integration, and catch per trip variables are correlated as a result of long-term downward pressures on the urchin stocks across the entire region.

stylized model includes one speed of adjustment parameter (λ_{north}), one constant set equal across ports (α_{north}), and one diagonal or own-revenue adjustment parameter (γ_{north}) in conjunction with symmetric off-diagonals for the substitute ports. The simulated northern California port shares are then:

$$s_{pt} = \alpha_{north} + \lambda_{north} s_{pt-1} + \gamma_{north}\left(\ln R_{pt} - \frac{1}{3}\sum_{p' \neq p} \ln R_{p't} \right). \qquad (20)$$

We impose the following restriction to match the restrictions in equation (19):

$$4\alpha_{north} + \lambda_{north} = 1. \qquad (21)$$

Table 3 summarizes the results of own-revenue elasticities at three different revenue levels because the discrete adjustment elasticities are functions of the data. The Appendix explains the calculations. Elasticity 1 and Elasticity 2 in table 3 contain, respectively, short- and long-run elasticities for the port switching model assuming that there is no adjustment at the patch level. That is, they take patch choice probabilities as given. All locations are inelastic with respect to own patch-specific revenues. This is not surprising given the infrequency of diver port switches. Moreover, trips are inevitably less elastic with respect to own patch revenues than with respect to port average revenues, because port average revenues are comprised of multiple patches. The pattern of elasticities also suggests that edge patches are more elastic. The reason is that much of diver spatial adjustment in the interior patches can take place without moving from one port to another. On the outer patches, this is less true.-

In the short and long run, revenue increases within a patch draw more effort from other ports and from southern California. The long-run elasticities are composed of short-run effects modified by the two different adjustment parameters. Recall that adjustment is far more rapid within northern California than between northern and southern California. The ratio of long-run to short-run elasticities reflects equations (A3) and (A4) in the Appendix. This ratio is between $[1/(1-\lambda_{south})]$ and $[1/(1-\lambda_{north})]$. Neither set of elasticities changes in response to scaling revenues up or down because equation (20) is linear in logarithms; *i.e.*, the revenue terms cancel from the elasticity calculations.

Columns 3 through 5 contain elasticities that allow for discrete patch adjustment. Frequently visited patches are less elastic than infrequently visited patches. It is also worth noting that the elasticities become larger as mean revenues increase. Column 4 combines discrete adjustment with short-run port adjustment, and column 5 combines discrete adjustment with long-run port adjustment. Overall, the magnitudes from patch adjustment are greater than those from port adjustment. The main lesson from these computed elasticities is that in the short run, effort responsiveness to revenue changes is relatively small for port decisions, whereas in the long run it is reasonably large. Short-run effort responsiveness is inelastic, averaging in the 0.1–0.2 range, whereas long-run responsiveness is less inelastic. When combined with discrete response, long-run elasticities are in the 1.0–2.6 range.

Table 3
Elasticities With and Without Port Model Trips
to Patch *j* with Respect to Revenues in Patch *j*

Patch	Elast. 1	Elast. 2	Elast. 3	Elast. 4	Elast. 5
Mean Revenues					
Farallons	0.251	0.508	2.076	2.328	2.584
1	0.098	0.197	0.807	0.904	1.004
2	0.207	0.457	1.607	1.814	2.064
3	0.017	0.068	1.520	1.537	1.588
4	0.126	0.301	1.483	1.608	1.784
5	0.119	0.271	1.066	1.186	1.337
6	0.057	0.127	0.974	1.031	1.101
7	0.111	0.239	0.775	0.886	1.014
8	0.090	0.178	0.699	0.788	0.876
9	0.122	0.241	0.983	1.104	1.223
10	0.233	0.461	1.895	2.127	2.355
1.5 x Mean Revenues					
Farallons	0.251	0.508	3.114	3.366	3.622
1	0.098	0.197	1.210	1.308	1.408
2	0.207	0.457	2.410	2.617	2.867
3	0.017	0.068	2.279	2.297	2.347
4	0.126	0.301	2.224	2.350	2.525
5	0.119	0.271	1.600	1.719	1.871
6	0.057	0.127	1.461	1.518	1.588
7	0.111	0.239	1.162	1.274	1.401
8	0.090	0.178	1.048	1.138	1.226
9	0.122	0.241	1.474	1.596	1.715
10	0.233	0.461	2.842	3.075	3.303
0.5 x Mean Revenues					
Farallons	0.251	0.508	1.038	1.290	1.546
1	0.098	0.197	0.403	0.501	0.601
2	0.207	0.457	0.803	1.011	1.260
3	0.017	0.068	0.760	0.777	0.828
4	0.126	0.301	0.741	0.867	1.042
5	0.119	0.271	0.533	0.653	0.804
6	0.057	0.127	0.487	0.544	0.614
7	0.111	0.239	0.387	0.499	0.626
8	0.090	0.178	0.349	0.439	0.527
9	0.122	0.241	0.491	0.613	0.732
10	0.233	0.461	0.947	1.180	1.408

Elasticity Definitions:
1) Short-run elasticity with no discrete adjustment.
2) Long-run elasticity with no discrete adjustment.
3) Elasticity with no port adjustment (short- and long-run are the same).
4) Short-run elasticity with both port and discrete adjustment.
5) Long-run elasticity with both port and discrete adjustment.

Simulation Results With Port Switching

We simulate the effects of creating a reserve in patch 8, a heavily fished patch.[27] We chose a heavily fished patch following the results in Sanchirico and Wilen (2001), which suggest that reserves are most likely to generate harvest increases when they are implemented in heavily exploited patches. Table 4 compares results of the simulation model with and without port switching. The first two lines repeat the results from Smith and Wilen (2003, table 4) and add projected trips per year for each diver; *i.e.*, a measure of per capita participation. These participation rates for the model without port switching approximately match actual participation of 26.52 per capita trips in 1996 for northern California.

By introducing port switching, the steady-state diver count in northern California is predicted to decline dramatically from what we observe towards the end of our sample period. There are two driving forces of this predicted trend. The first is that the total number of divers is assumed to decrease from approximately 400 at the end of the sample period to the limited entry target level of 300 in the steady state. But this 25% reduction clearly cannot explain the entire difference between 131 and 33 divers. The second driving force is the evolution of state variables in northern California. As the simulation model proceeds beyond the sample period, continued fishing pressure reduces abundance and, therefore, revenue per trip. By fixing catch per trip in southern California, increased pressure on the northern California resource ultimately leads to divers switching to southern California.

The switching behavior within northern California serves to reinforce the evolution of state variables, and thus, the prediction of a smaller number of total divers in the north. If some patches have high abundance but are difficult to reach from ports

Table 4
Economics of Marine Reserves with Port Switching
The Northern California Red Sea Urchin Fishery

	Steady-State N. California Divers	Trips per Diver per Year	Steady-State Harvest (1,000 lbs.)	Steady-State Egg Production (billions)	Discounted* Revenues ($1,000)
Discrete Choice Only (*a* = 0.005)					
No Closure	131	29.9	830	1,316	17,440
Close Patch 8	131	25.3	752	1,441	15,074
Port Choice and Discrete Choice (*a* = 0.005)					
No Closure	33	57.8	638	1,627	13,400
Close Patch 8	36	47.2	576	1,692	11,660
Port Choice and Discrete Choice (*a* = 0.005) 50% Decrease in S. Cal. Revenues					
No Closure	83	37.9	802	1,399	16,846
Close Patch 8	89	31.2	728	1,495	14,683

* Uses a 5% constant discount rate and assumes $1 per pound of sea urchin.

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[27] Patch 8 is illustrative, but the results using other heavily fished patches are consistent with the results reported here (Smith 2001).

that have the most divers, in the model without port switching there is a limited amount of adjustment that will take advantage of these opportunities. High abundance patches are predicted to persist without port switching because there is a fixed small number of divers with reasonable access to these locations. In contrast, with port switching, divers are predicted to relocate to ports near high abundance areas and put greater pressure on the resource in those areas. Eventually, this behavior lowers the average abundance in northern California and decreases the overall attractiveness of the region.

Across all three sets of simulations, the per capita trip count decreases when a reserve is introduced. The reason is straightforward. A reserve in patch 8, a heavily fished location, decreases the inclusive value in the nested logit model and decreases the overall attractiveness of participating. In the long run, the benefits from reserve creation are not enough to offset the loss of this fishing alternative, so overall profitability of fishing is lower. The long-run consequence of port switching in this model is reduced aggregate harvesting pressure on the northern California resource. As a result, egg production is considerably higher than in the simulations without port switching. However, the total harvest and discounted revenue predictions are also lower. This suggests that the system as a whole in the steady state is more lightly exploited than the exploitation level corresponding to the system-wide maximum sustainable yield.

The extreme predicted decline of northern California divers in the port switching model is partly an artifact of the assumption of fixed southern California revenues. At the outset, this assumption seems reasonable because southern California catch per trip appears stable in the sample period, especially in comparison to northern California catch per trip. This suggests that southern California is already near a harvested steady state.[28] However, a major influx of northern California divers would decrease abundances in southern California. To assess this possibility, simulations are run with a 50% decrease in southern California catch per trip and hence, revenues.

Clearly, the reduction in southern California revenues supports corresponding increased fishing pressure on the northern California resource, as indicated by decreased egg production. There is also a dramatic increase in number of divers in the north, although the results of the 50% reduction still do not lead to a steady-state harvest that is as large as the model without port switching.

In all cases, with and without port switches, a marine reserve in patch 8 reduces discounted revenues and steady-state harvest but increases egg production. The discounted present value revenue cost of a reserve ranges from $1.74 million to $2.36 million, the largest cost being in the model without port switching. If these predictions are credible, the key policy question is whether the gains in system-wide egg production and other ecological benefits outweigh foregone harvest and hence, revenue. Although costs are largest for the model without port switching, the egg production benefits are also largest in this case. This suggests an essential tradeoff that exists for levels of exploitation below the system's maximum sustainable yield. Any marine reserve will increase egg production, but these increases will be larger for more heavily exploited systems.

Can We Find a Long-run Harvest Gain From a Marine Reserve?

The simulations in Smith and Wilen (2003) suggest that responsiveness to economic incentives reduces the likelihood that marine reserves will pay off in terms of increased harvest, compared with a model that assumes no behaviorally based policy

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[28] We would expect the price component of revenues to affect both southern and northern California revenues similarly, so the focus is on catch per trip.

responsiveness. This is partly because some displaced fishermen simply switch to adjacent patches and increase exploitation over the remaining system. When we incorporate more behavioral flexibility, as in table 4, divers are able to adjust to revenue differentials more flexibly, exiting the northern California fishery as returns decline in the long run. This increased spatial mobility removes some of the exploitation pressure predicted by displaced effort in the model without port switching. However, we were generally unable to simulate circumstances in which there was a predicted overall harvest gain with reserves under our initial model parameterizations that reflected best available knowledge. Even with an assumed reduction in southern California returns, the predicted aggregate pressure on the northern California resource is not sufficient to give rise to a steady-state harvest increase.[29]

   In table 5, we show the results of trying to generate a fisheries enhancement outcome with reserves by considering different parameters reflecting dramatic changes in the economic environment of sea urchin harvesters. Specifically, for each model prices are doubled, and the participation rate is manipulated exogenously to create conditions expected to be more favorable to a reserve.[30] A price increase of this magnitude could result from a demand shift for sea urchin in Japan, a change in the U.S./Japanese exchange rate, or a combination of both.[31] A large exogenous increase in participation suggests that opportunities for urchin divers outside of the urchin fishery decline substantially, reflecting possibly a major recession, the collapse of other fisheries in which part-time divers participate, or both.

   For these simulated re-parameterizations, the model without port switching predicts that an increase in steady-state harvest may be possible from creating a marine reserve in patch 8. At the same time, it is not just the change in steady-state harvest that is important; the whole time path after a reserve is created needs examination. Figure 4 depicts the harvest paths approaching the pre-reserve steady state and the divergence of the reserve and non-reserve paths after implementing the closure. Because the biological system takes several years to generate the first payoffs from protecting a spawning population within a reserve, it turns out that in spite of the long-run increase in harvest, the discounted revenues for the closure are lower than for no closure. This reflects the fact that the biological responsiveness to a reserve is slow relative to the economic consequences and the discount rate. With an economically driven model of diver behavior, harvesters respond immediately to a closure by lowering their participation rates and redistributing some of their fishing effort across the remaining open areas. The short-run consequence is lower aggregate harvest. Over time, stocks in the reserve rebuild and export larvae to other areas. Eventually, when these urchins reach the minimum size limit, overall harvestable biomass is large enough to raise catch above the pre-reserve level. But, the time that it takes for this buildup and the consequent long period of losses leads to a negative net present value of the policy (in revenue terms).

   Because participation is much higher in the table 5 scenarios compared to those in table 4, egg production is much lower. As a result, the egg production increase from instituting a reserve is much higher. Egg production increases 159 billion in

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[29] A more extreme case would be a total collapse of the southern California fishery. We do not consider an exogenous collapse of southern California here, but the next paragraphs consider other extreme exogenous shocks and their impacts on the performance of a marine reserve.

[30] Shocking the participation rate simply involves increasing (or decreasing) the constant parameter in the discrete choice model. The baseline value is the estimated coefficient of 1.055. Several different shocks are attempted in search of a reserve scenario that increases steady-state harvest. The results in table 5 use a value of 2.5 for the constant.

[31] Reynolds and Wilen (2000) discuss the importance of the U.S./Japanese exchange rate for the price of raw urchin in California. The authors also document demand-side conditions in Japan and general equilibrium supply forces that can combine to produce major changes in the market for urchin roe.

Table 5
Economics of Marine Reserves with Macroeconomic Shocks
The Northern California Red Sea Urchin Fishery

	Steady-State N. California Divers	Trips per Diver per Year	Participation Rate	Steady-State Harvest (1,000 lbs.)	Steady-State Egg Production (billions)	Discounted* Revenues ($1,000)
Discrete Choice Only ($a = 0.005$)						
Double prices and exogenous increase in participation rate						
No Closure	131	107.1	46%	883	720	18,548
Close Patch 8	131	96.5	41%	921	879	17,362
Port Choice and Discrete Choice ($a = 0.005$)						
75% Decrease in S. Cal. Revenues, double prices, and exogenous increase in participation rate						
No Closure	56	174.5	75%	972	796	20,402
Close Patch 8	68	143.1	61%	952	910	18,865

Notes: * Uses a 5% constant discount rate and assumes $1 per pound of sea urchin.
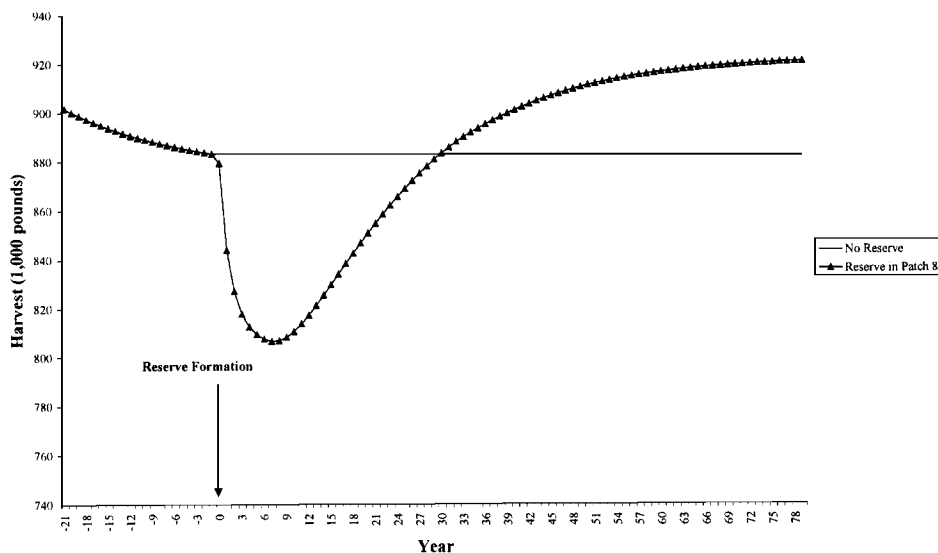** Compare to participation rate of 11% using nested logit parameters and mean values of variables.

Figure 4. A Marine Reserve with Macroeconomic Shocks

table 5 but only 125 billion in table 4. For the port switching model, we use the same exogenous increase in participation, double prices, and also decrease southern California catch per trip by 75%. Even under such extreme assumptions, a reserve does not lead to a steady-state harvest increase. Again, compared to the table 4 scenarios, egg production is much lower with the increased participation rate.

Given the high participation rates in table 5, we have to question whether the economic environment posited in these rather extreme simulations is even feasible. These simulations predict that the representative diver chooses to harvest between 40% and 75% of open fishing days. Given that the largest share of open fishing days occurs in the winter months, this simply is unrealistic. We know from the discrete choice model that weather conditions profoundly affect the probability that harvesters will fish. The simulation model incorporates estimates of diver sensitivity to bad weather, but when we arbitrarily increase participation rates, the marginal effects of bad weather are reduced. It seems unlikely that harvesters, even in the face of considerable macroeconomic shocks, would fish on extremely dangerous days. They may be willing to accept more physical risk from weather conditions when their economic circumstances are desperate, but it seems unlikely that they would accept such a dramatic increase in exposure to weather risk.

Another factor that impugns the reasonableness of these participation rates is the physical strain of diving. Diving is a physically taxing endeavor and can have a cumulative effect on the body over short time horizons. We observe very few divers participating repeatedly over many days in a row. Yet, we know that weather conditions can be autocorrelated, and thus, favorable weather often occurs in spells of several consecutive days. As such, we would expect the physical strain of diving to limit divers' abilities to select for favorable weather days. Hence, the realities of diving fatigue also cast doubt on the likelihood of extremely high participation rates.

    In summary, it is difficult to find any reasonable set of circumstances under which marine reserves will generate long-run harvest gains in the California sea urchin fishery. Overexploitation that would theoretically lead to predicted harvest gains from creating a reserve is curtailed in reality by existing management measures coupled with individual divers' opportunity costs of fishing effort. Moreover, the potential spatially explicit gains from a reserve are offset largely by the spatial responsiveness of the urchin fleet.

Discussion

A marine reserve is a management tool that can contribute to multiple objectives, at least in principle. As a means to preserve unique ecosystems, for instance, a spatial closure is arguably unparalleled as a policy instrument. A more controversial question is whether marine reserves can benefit commercial fisheries, and in some sense, improve on existing management tools. A long literature on this topic has emerged in marine biology and fisheries science that promotes using reserves to manage commercial fishing. However, virtually all of this literature has ignored the importance of economic behavior. This paper shows that the most optimistic results are a consequence of specialized assumptions. Incorporating a more realistic economic model into the analysis reduces the set of scenarios in which marine reserves generate favorable outcomes.

    This paper specifically assesses marine reserves when multiple spatial and temporal scales of behavioral response are possible. In a recent study, Smith and Wilen (2003) found that spatial behavior, modeled as a repeated nested logit of daily participation and location choices, offsets the potential harvest gains from a marine reserve in the northern California sea urchin fishery. The present analysis takes their modeling a step farther by relaxing some restrictions of their behavioral model and allowing for port switching activity. We find that more elastic effort response over space and time has some important impacts on predictions from the integrated bioeconomic model. First, some of the heterogeneity in the pre-reserve distribution of effort is averaged out. For example, without port switching, Smith and Wilen find that some patches are not exploited heavily because they are too costly to access. As a result, they may play a role as *de facto* reserves, reducing some of the potential gain from reserves by protecting the whole system from overexploitation. With port switching, the attractiveness of ports and the portfolio of accessible patches off those ports are arbitraged out by port selection behavior. Other things equal, this is likely to distribute more initial effort and exploitation into patches that might otherwise be calibrated with less effort with a fixed diver distribution. A second implication of more elastic effort response associated with port and region switching is that effort responds more quickly to post-reserve conditions. In the short run, this will lead to even more exploitation of nearby patches that are still accessible after a reserve is created. This reallocation mitigates some of the immediate costs of the closure, but it ultimately puts more exploitation pressure on the parts of the system that remain open, potentially prolonging the transition to the steady state. Overall, we find that a model with enriched behavioral detail still reaches conclusions that are substantially at variance with the received wisdom that has emerged from purely biological models that depict harvester behavior as unresponsive to economic opportunities over time and space.

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Appendix

Elasticities with the Port Allocation Model

To compute spatial revenue elasticities, we combine the repeated nested logit probabilities with the SUR share models. Recall that we denote trips as y, revenues as R, choice occasions as o, and divers in a port as d. We index patch as j, time as t, and port as p. Recognizing that patch-specific choice probabilities are conditional on port, we denote these probabilities as $p_{jt|p}$. The elasticity of trips to j at time t with respect to revenues in j at t (ζ_{jt}) is:

$$\zeta_{jt} = \frac{\partial y_{jt}}{\partial R_{jt}} \frac{R_{jt}}{y_{jt}} = o_t \sum_{p=1}^{4} \left[\frac{\partial d_{pt}}{\partial R_{jt}} p_{jt|p} + \frac{\partial p_{jt|p}}{\partial R_{jt}} d_{pt} \right]. \tag{A1}$$

To calculate $(\partial p_{jt|p})/(\partial R_{jt})$ for each port, we first note that this joint probability is the product of the marginal patch-choice probability (p_j) and the marginal participation probability ($p_{GO|j}$), all conditioned on a given port.

$$\frac{\partial p_{jt|p}}{\partial R_{jt}} = \frac{\partial p_{GO|j}}{\partial R_{jt}} p_j + \frac{\partial p_j}{\partial R_{jt}} p_{GO|j}. \tag{A2}$$

Then, we use the nested logit probability expressions to find (for an own-patch revenue change) $(\partial p_{GO|j})/(\partial R_{jt})$ and $\partial p_j/\partial R_{jt}$.

Since the discrete choice model does not contain any lagged variables, the short- and long-run derivatives are the same. Thus, we must only find short- and long-run expressions for $\partial d_{pt}/\partial R_{jt}$. Denoting total divers as d_{tot}, northern California share as s_n, and port share as s_p, we note first that d_{pt} is defined as follows:

$$d_{pt} = (d_{tot})s_{nt}s_{pt}. \tag{A3}$$

Hence, for the short run, we have:

$$\frac{\partial d_{pt}}{\partial R_{jt}} = (d_{tot})\left[\frac{\gamma_{SOC}}{R_{north,t}} \frac{\partial R_{north,t}}{\partial R_{jt}} s_p + s_n \frac{\gamma_{north}}{R_{pt}} \frac{\partial R_{pt}}{\partial R_{jt}} \right], \tag{A4}$$

and for the long run we have:

$$\frac{\partial d_{pt}}{\partial R_{jt}} = (d_{tot}) \left[\frac{1}{(1 - \lambda_{south})} \frac{\gamma_{SOC}}{R_{north,t}} \frac{\partial R_{north,t}}{\partial R_{jt}} s_p + s_n \frac{1}{(1 - \lambda_{north})} \frac{\gamma_{north}}{R_{pt}} \frac{\partial R_{pt}}{\partial R_{jt}} \right] \quad \text{(A5)}$$

We can see from this expression that even though $\lambda_{south} < \lambda_{north}$, the long-run effects from within northern California switching are not necessarily lower because $(\partial R_{north,t})/(\partial R_{jt}) < (\partial R_{pt})/(\partial R_{jt})$.